Spatio-Temporal Sampling-Point Allocation for High-Density Robotic Pest Monitoring and Precision Treatment

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Abstract.
Efficient pest monitoring is essential for enabling timely, localized treatment and reducing unnecessary pesticide application in high-density agricultural systems. Conventional manual scouting is often limited by labor requirements, operational cost, and restricted spatial coverage, which may delay the detection of early infestation foci. This limitation is particularly important for pests such as the two-spotted spider mite (Tetranychus urticae), where localized infestations can expand into larger patches if not detected in time.

This study evaluates a spatio-temporal sampling-point allocation strategy for robotic pest monitoring in commercial sweet pepper net-houses. The proposed approach combines spatial stratification of the field into six regions with temporal stratification of the growing season into four seasonal spread stages. Sampling density was assigned according to each region–stage combination, allowing monitoring effort to vary across both field location and seasonal timing. The strategy was evaluated using real plant-level infestation data collected in Paran, Israel, and compared with naïve random sampling and a simulated manual-inspection baseline. Detection was assessed using a treatment-oriented framework, in which detecting an infested plant represented detection of a local infestation patch.

At a dwell time of 35 s per plant, the proposed strategy achieved its greatest advantage during the Early stage, improving detection by approximately 28 percentage points compared with naïve random sampling and 40 percentage points compared with manual inspection. In later stages, differences between the robotic strategies were smaller, while both consistently outperformed manual inspection. These findings demonstrate that incorporating spatial and seasonal knowledge into robotic sampling design can improve early pest detection and support more targeted and efficient pest management in high-density crop systems.

Keywords.
Precision agriculture; robotic monitoring; spatio-temporal sampling; pest detection; two-spotted spider mite; treatment-oriented detection

1. Introduction

Effective monitoring of plant diseases and pests is crucial for maximizing agricultural productivity and reducing the adverse impacts associated with biotic stresses in farming systems. Globally, pests and diseases are responsible for annual yield losses ranging between 20% and 30%, emphasizing the need for accurate and timely detection strategies *(Oerke, 2006)* Without efficient monitoring mechanisms, diseases and pests may spread quickly, causing significant crop damage and substantial economic losses *(Zhang et al., 2019)*

Traditional monitoring methods in agriculture predominantly rely on manual observations. Although manual sampling can provide accurate information, it often requires considerable labor, time, and financial resources, and may lack sufficient spatial density and temporal frequency in high-density cropping systems. These limitations may delay the identification of infested areas, allow pest spread, and require broad pesticide application rather than localized treatment *(Albajes et al., 1999)* . Over-application of pesticides may negatively affect the environment, disrupt ecological balance, and accelerate pest resistance to chemical treatments *(Gerson & Weintraub, 2007).*

The two-spotted spider mite *(Tetranychus urticae),* which is the selected pest in this study, poses a significant threat in greenhouse and protected crop systems, particularly in crops such as sweet pepper. This pest reproduces rapidly, damages plant tissues and can cause severe harm if not detected and controlled in time *(Gerson & Weintraub, 2012)*. Effective monitoring and timely detection can improve pest management and reduce potential crop damage.

Agricultural robotics equipped with advanced sensors and automated data-collection capabilities may enable frequent, precise, and systematic monitoring, while reducing reliance on manual labor *(Ghimire et al., 2024; Inamdar et al., 2024).* However, their routes and sampling points must be planned efficiently in terms of time and operational cost, especially when detection depends on the dwell time allocated to each sampled plant.

Most optimization studies in agriculture for monitoring tasks assume that only a few points can be sampled on each visit, since they are typically designed for human scouting or for the placement of fixed sensing devices, such as soil-moisture probes or insect traps. Under this labor, time, or hardware constraints, the algorithms focus on selecting a small set of sampling locations *(e.g. Ohana-Levi et al., 2021).* In contrast, in high-density robotic monitoring the objective is to allocate a relatively large set of sampling points across the field and across monitoring dates. Accordingly, methods developed for sparse, human- or device-limited sampling are not necessarily suitable for robotic monitoring platforms operating in high-density crop systems.

This study presents a spatio-temporal sampling-point allocation strategy for robotic pest monitoring in commercial sweet pepper net-houses. The proposed approach divided the field into six predefined spatial regions representing different risk areas within the net-house, based on prior empirical knowledge of the spatial distribution of *Tetranychus urticae* in pepper net-houses *(Shmuel, 2018).* The growing season was divided into four temporal stages representing major phases of infestation development.

A dedicated sampling density is assigned to each region-stage combination, allowing monitoring effort to vary across both space and time. The proposed strategy was evaluated using plant-level infestation data obtained from high-density monitoring of two-spotted spider mite populations during the 2015-16 and 2016-17 growing seasons. The objective of this paper was to assess whether incorporating spatial and temporal information into robotic sampling design can improve pest detection compared with alternative monitoring approaches.

2. Materials and Methods

2.1 Study Data

The study was based on a high-density plant-level monitoring dataset collected from commercial sweet pepper net-houses in Paran, located in the Arava region of southern Israel, during the 2015-16 and 2016-17 growing seasons. The data were originally collected by *Shmuel)2018)* as part of field observations examining the spatial and temporal dynamics of two-spotted spider mite (*Tetranychus urticae*) infestation in sweet pepper crops. Monitoring was conducted weekly throughout the crop season, from planting to harvest.
Across the two pepper growing seasons, five field-season datasets were mapped, representing four distinct net-houses, with one net-house monitored in both seasons. The monitored net-houses were organized into gables, crop rows, and internal pathways used for field access and manual inspection. This structure was used to represent plant locations within the field and to simulate the manual-inspection strategy.
For each plant-level observation, the dataset included the sampling date, plant location, and infestation severity. In the present study, severity values were converted into a binary infestation status: plants with positive severity values were considered infested, whereas plants with zero severity were considered non-infested. This plant-level infestation status was used as ground truth for simulation-based evaluation of the monitoring strategies.

2.2 Spatial and Temporal Stratification

The underlying hypothesis of this study was that incorporating prior knowledge on the spatial and temporal dynamics of infestation spread would increase detection efficiency, allowing higher detection rates to be achieved with the same or fewer sampling points than uniform sampling across space and time. To operationalize prior knowledge on the spatial and temporal dynamics of infestation spread, each net-house was stratified into six spatial risk regions and four seasonal growth stages, allowing sampling intensity to vary according to expected infestation risk. Spatially, the field was divided into six predefined regions corresponding to northern and southern margins, pathways, and central areas (Figure 1A). This division allowed sampling effort to vary according to the expected spatial distribution of infestation risk, which was assumed to be higher along the margins and pathways than in the central parts of the net-house. Temporally, the growing season was divided into four stages according to weeks from planting and the observed infestation trend (Figure 1B). Stage boundaries were set at Weeks 7, 11, and 17, defining the Early, Rising, Peak, and Decline stages. Combining the six spatial regions with the four temporal stages created a region-stage framework, in which sampling density could be assigned separately for each region-stage combination.

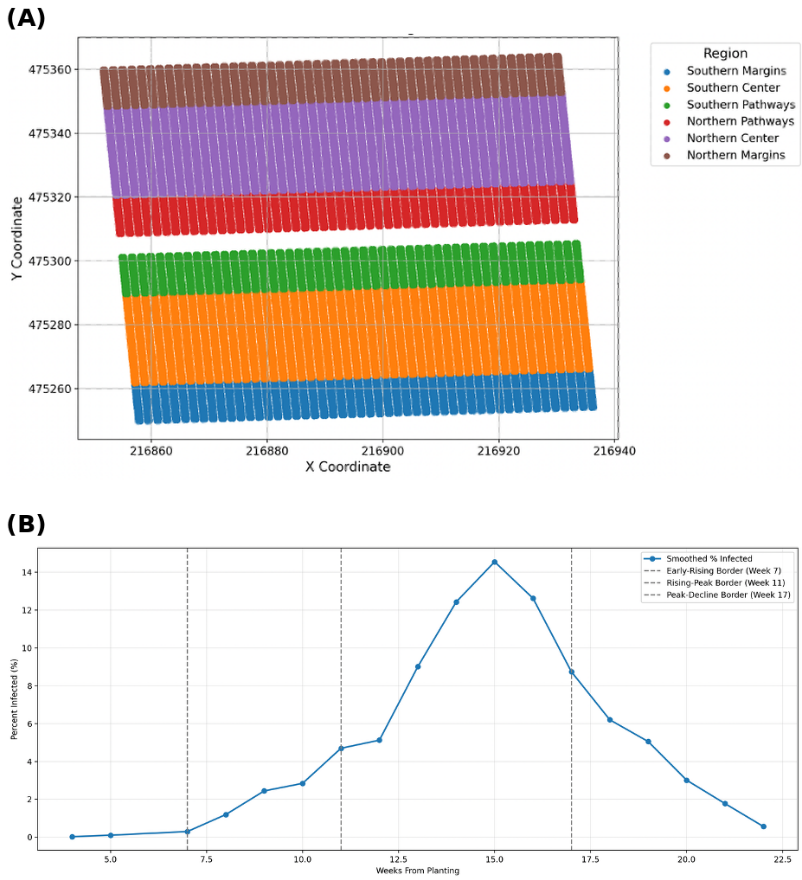

Fig. 1 Spatial and temporal stratification used in the proposed spatio-temporal sampling framework. (A) Division of the net-house into six predefined spatial regions: northern and southern margins, pathways, and central areas (B) Temporal division of the growing season into four stages-Early, Rising, Peak, and Decline-based on the infestation trend over weeks from planting; dashed lines indicate the stage boundaries at Weeks 7, 11, and 17.

2.3 Proposed Spatio-Temporal Sampling-Point Allocation

The proposed sampling strategy was designed to guide robotic monitoring by allocating sampling effort according to spatial risk and seasonal spread stage. Instead of applying a uniform sampling rate across the entire net-house, the strategy used the region-stage framework described above to assign a dedicated sampling density to each combination of spatial region and temporal stage. In this way, the sampling plan could reflect differences in infestation patterns across field locations and throughout the growing season.

The sampling densities were determined in a preliminary calibration step using historical plant-level infestation data. In this calibration, sampling densities that provided adequate detection while avoiding unnecessary sampling effort were identified based on two performance criteria:

the average weekly detection rate and the percentage of weeks with detection above 80%. Regions and stages associated with different levels of infestation risk or monitoring importance could therefore receive different sampling densities, depending on the need to prioritize known infestation patterns while maintaining sufficient coverage for detecting new infestation foci.

At each sampling date, the corresponding temporal stage was first identified according to the week from planting. The field was then divided into the predefined spatial regions, and the sampling density assigned to each region-stage combination was applied separately within that region. Sampling points were selected from the eligible plants in each region according to the assigned density, resulting in a structured, non-uniform set of sampling points for the robot.

2.4 Baseline Sampling Strategies

To evaluate performance gains of the proposed spatio-temporal allocation strategy, two baseline monitoring strategies were simulated: naïve random sampling, representing high-density robotic sampling without prior spatial knowledge, and simulated manual inspection routine, representing the sparse sampling typically achievable by human scouts. Both baselines were evaluated using the same field-season datasets, sampling dates, and binary infestation status used for the proposed strategy.

2.4.1 Naïve Random Sampling

The naïve random sampling strategy was used as a density-matched baseline. For each sampling date, the total number of sampled plants was set to match the overall sampling density used by the proposed spatio-temporal strategy on that date. However, unlike the proposed strategy, the naïve baseline did not allocate different sampling densities to different spatial regions. Instead, sampling points were selected randomly from the eligible plants across the entire field.
This baseline therefore represented a non-spatial allocation of the same overall monitoring effort.

2.4.2 Simulated Manual Inspection

The manual-inspection baseline simulated the scouting procedure typically performed by human inspectors in pepper net-houses. Each net-house consisted of 10 gables, and during each weekly inspection event the simulated inspector followed one predefined pathway within each gable, examining plants on both sides of the walking row.
Four predefined pathways were used and rotated sequentially across weeks, so that each pathway was revisited every four weeks. Along each selected row, the inspector stopped at 20 approximately evenly spaced observation points. At each stopping point, plants within a limited visual range were considered inspected (up to 6 plants), including the plant at the stopping position and its immediate neighbors along the row.

2.5 Detection and Treatment-Oriented Evaluation Framework

Detection performance was evaluated using a treatment-oriented framework, reflecting a practical pest-management setting. When an infested sampled plant was detected, the detection was interpreted as identification of the whole infestation patch surrounding it. Accordingly, infested plants located within the detected patch were also counted as detected, even if they were not individually sampled.

The initial local patch was defined according to the treatment-based patch structure used in the simulation. It included plants in neighboring rows and nearby columns around the detected plant, while respecting the structural boundary between the southern and northern parts of the net-house. After the initial patch was formed, patch expansion was evaluated along the row direction. If an infested plant was detected at the patch edge, the patch was expanded further in that direction using the same local patch structure. This process continued until no additional infected edge plants were detected.

This patch-based detection criterion was applied to all three strategies: the proposed spatio-temporal strategy, the naïve random strategy, and the simulated manual-inspection baseline. For the proposed spatio-temporal and naïve random strategies, a one-week blocking rule was also applied. Patches detected in each week were excluded from sampling in the following week, simulating a probable short-term operational effect of treatment or follow-up action. The blocking rule was not applied to the manual-inspection baseline, which followed a fixed rotating pathway-based scouting procedure independent of previous detections.

For the robotic sampling strategies, detection was modeled probabilistically as a function of dwell time per plant, using detection probabilities derived from (*Yehoshua et al. 2023*(. Longer dwell times were associated with higher true-positive detection probabilities, while false-positive detections were not considered in the simulation. The same dwell-time-dependent detection assumptions were applied to both robotic strategies, allowing performance differences to be attributed mainly to the allocation of sampling points rather than to differences in the detection model.

2.6 Performance Evaluation

The performance of the sampling strategies was evaluated using the plant-level infestation status as ground truth. For each field-season dataset and sampling date, the total number of infested plants was calculated, and the number of detected infested plants was determined according to the treatment-oriented patch-detection framework described above.
The main performance metric was the detection rate, defined as:

(1) $$Detection\ Rate = \frac{Number\ of\ detected\ infested\ plants}{Total\ number\ of\ infested\ plants}$$

where detected infested plants included both directly sampled infested plants and infested plants located within detected local patches.
Sampling effort was evaluated using the sampling ratio, defined as:

(2) $$Sampling\ Ratio = \frac{Number\ of\ inspected\ plants}{Total\ number\ of\ plants}$$

Performance was summarized by seasonal spread stage in order to evaluate how each monitoring strategy performed across different phases of infestation development. This stage-based comparison was used to assess whether the proposed spatio-temporal allocation improved detection relative to the naïve random baseline and the simulated manual-inspection baseline, particularly during early infestation development.
For the robotic sampling strategies, detection performance was also evaluated across different dwell times per plant. This analysis was used to examine how inspection time affected detection rate and to select a representative operating point for comparing the strategies. Based on the dwell-time analysis, a dwell time of 35 s per plant was used for the main stage-based comparison among the proposed spatio-temporal strategy, the naïve random baseline, and the simulated manual-inspection baseline.
Because the naïve random strategy selected sampling points randomly, it was repeated across simulations to reduce the effect of random sampling variation, and average performance was used for comparison. The proposed spatio-temporal strategy was evaluated using the predefined region-stage sampling densities, while the manual-inspection baseline followed the rotating

pathway-based scouting procedure described above. The comparison focused on two aspects: the proportion of infested plants detected by each strategy and the sampling effort required to achieve this detection.

3. Results

The results are presented in three parts. First, the effect of dwell time on detection performance is presented. Second, detection performance is compared across the three monitoring strategies and seasonal spread stages. Finally, the sampling ratio used by each strategy is summarized by stage.

3.1 Effect of Dwell Time on Detection Performance

Detection rate increased with dwell time across all seasonal spread stages (Figure 2). The lowest detection rates were observed at 20 s per plant, and the highest at 50 s per plant.

The increase was more pronounced between 20 s and 35 s and became more gradual at longer dwells times. At 35 s, detection reached approximately 74% in the Early stage and exceeded 80% in the Rising, Peak, and Decline stages. Therefore, 35 s per plant was used as the operating point for the stage-based comparison among monitoring strategies.

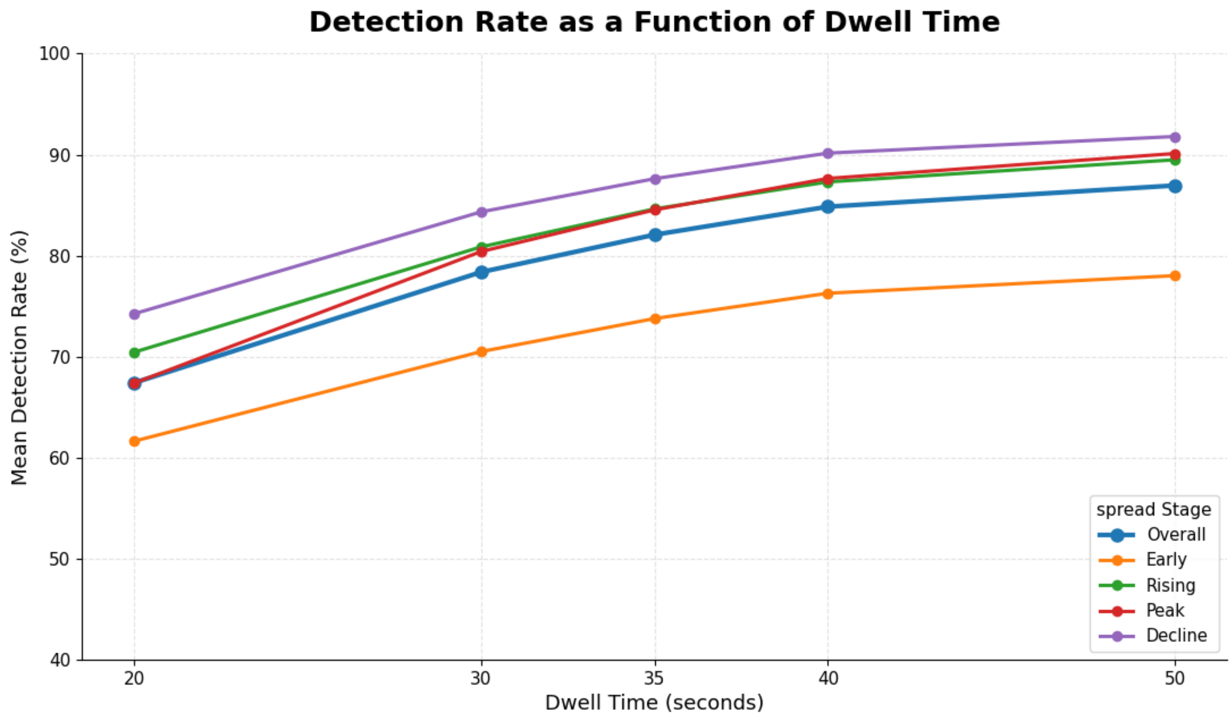

Fig. 2 Detection rate as a function of dwell time across seasonal spread stages. Detection performance increased with longer dwell time. A dwell time of 35 s was used as the operating point for comparing the monitoring strategies

3.2 Detection Performance Across Seasonal Spread Stages

Detection performance differed across monitoring strategies and seasonal spread stages (Figure 3). The manual-inspection baseline showed the lowest detection rates across all stages, ranging from approximately 32% to 39%. The naïve random strategy achieved higher detection than manual inspection, increasing from approximately 46% in the Early stage to 79% in the Rising stage and about 87% in the Peak and Decline stages.

The proposed spatio-temporal strategy achieved detection rates of approximately 74%, 85%, 85%, and 88% in the Early, Rising, Peak, and Decline stages, respectively. Compared with the naïve strategy, it showed higher detection in the Early, Rising, and Decline stages, while the naïve strategy was slightly higher in the Peak stage.

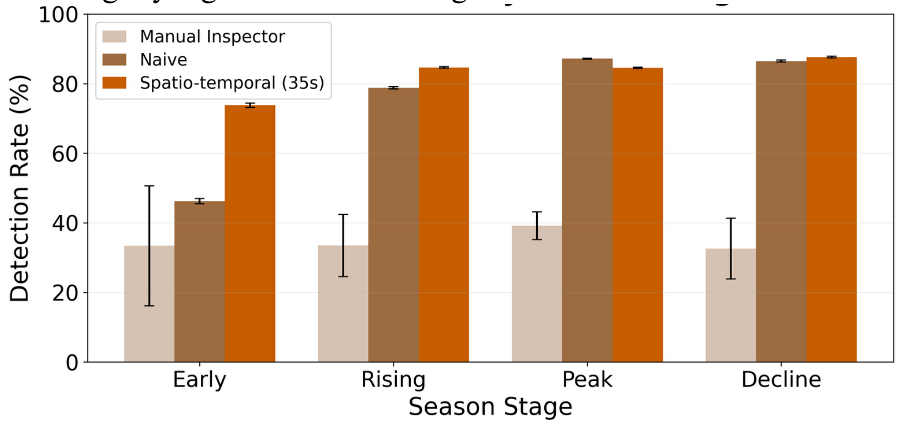

Fig. 3 Mean detection rate by seasonal spread stage for the simulated manual-inspection baseline, naïve random sampling, and the proposed Spatio-temporal sampling strategy at a dwell time of 35 s. Error bars represent 95% confidence intervals of the mean detection rate across weekly observations within each stage

3.3 Sampling Ratio Across Seasonal Spread Stages

The sampling ratio used by each monitoring strategy is summarized in Table 1. The manual-inspection baseline used a constant sampling ratio of 9.2% across all seasonal stages, reflecting the fixed pathway-based scouting procedure used to simulate actual manual inspection in the monitored pepper net-houses.

The naïve random and spatio-temporal strategies were assigned comparable stage-dependent initial sampling ratios. The values reported in Table 1 represent the realized sampling ratios, including both the initially selected sampling points and additional plants directly inspected during patch expansion. Therefore, the small differences between the two robotic strategies reflect differences in the specific sampling points selected and in the number of patch-expansion checks triggered during the simulations. Sampling ratios increased across the season for both robotic strategies, from 7.0% in the Early stage to 13.4-14.0% in the Decline stage.

Table 1. Sampling ratio by monitoring strategy and seasonal spread stage. Values represent the % plants inspected by each strategy

Stage	Manual (%)	Naïve (%)	Spatio-temporal (%)
Early	9.2	7.0	7.0
Rising	9.2	8.8	8.9
Peak	9.2	10.1	11.0
Decline	9.2	13.4	14.0

4. Discussion and Conclusions

The results demonstrate that incorporating spatial and temporal information into the sampling design improved pest detection, particularly during the *early stage* of infestation development. In this stage, the proposed spatio-temporal strategy achieved a detection rate of 73.8%, compared with 46.2% for the naïve random strategy and 33.4% for the manual-inspection baseline. This improvement was achieved while using the same sampling ratio as the naïve strategy, 7.0%, and a lower sampling ratio than the manual-inspection baseline, 9.2%. Therefore, the *early stage* advantage was not explained by increased sampling intensity alone, but by the spatial and seasonal allocation of sampling points.

The advantage of the proposed strategy was also observed in the *rising stage*, where it achieved 84.6% detection compared with 78.8% for the naïve strategy and 33.5% for manual inspection. In later stages, the difference between the two robotic strategies was smaller: the naïve strategy achieved slightly higher detection in the *peak stage*, whereas the spatio-temporal strategy achieved slightly higher detection in the *decline stage*. These results indicate that the main contribution of the proposed approach is in the earlier stages of pest spread, when timely detection of localized infestation foci is most important.

The simulated manual-inspection baseline showed lower detection rates across all stages, ranging from 32.6% to 39.1%, despite using a constant sampling ratio of 9.2%. This reflects the limited spatial coverage of pathway-based scouting in high-density net-houses. In contrast, the robotic strategies enabled broader and more flexible allocation of sampling points across the field, resulting in higher detection performance.

Overall, the findings show that prior knowledge of the spatial and temporal spread of the two-spotted spider mite can support the design of smarter sampling distributions for robotic pest monitoring specifically in the early infestation period. The proposed spatio-temporal strategy improved early detection while maintaining comparable sampling effort, supporting more effective, efficient and site-specific pest management in high-density pepper net-houses. Future work will focus on evaluating the framework in synthetic field scenarios generated from empirical spread patterns, extending it to additional crops and biotic stresses, and developing adaptive sampling strategies that update sampling decisions based on recent detections.

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